ABC3: Active Bayesian Causal Inference with Cohn Criteria in Randomized Experiments

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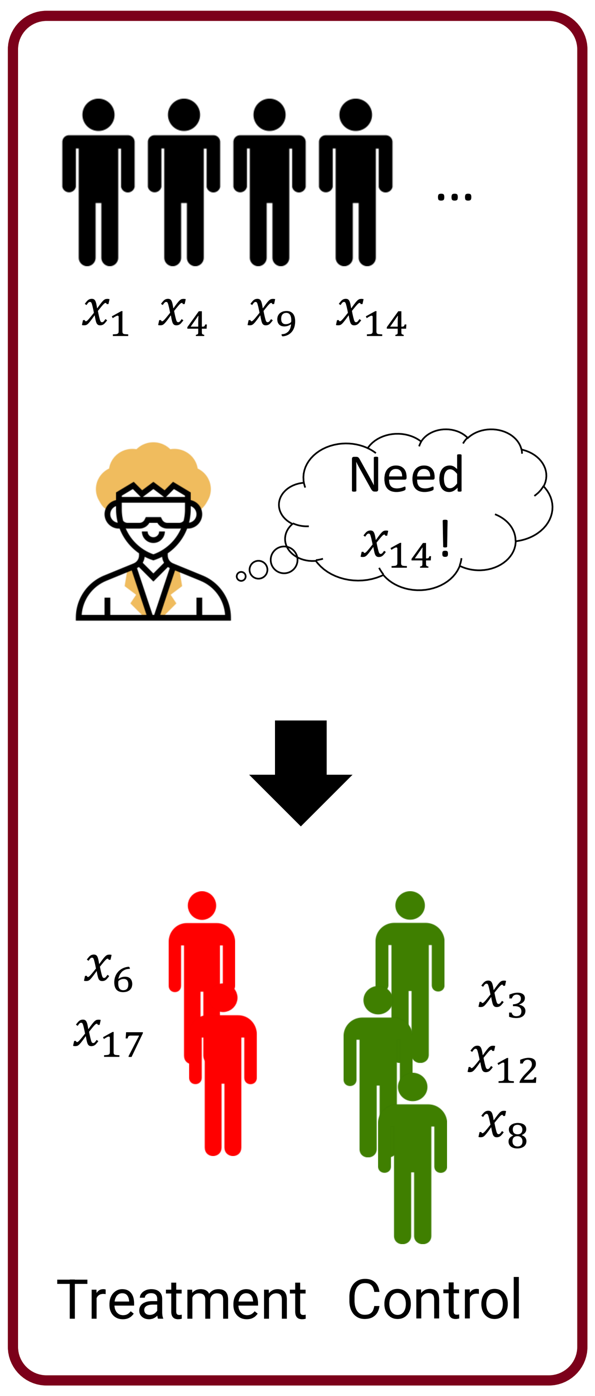
Motivation

- Randomized experiment is usually expensive, so an efficient experiment design is desirable
- What if we already know the covariate information *a priori*, can we utilize it?
- Active learning: practitioner chooses unlabeled data points and ask the oracle to label them



Problem Setting

- X: covariate, Y^a: potential outcome for treatment ($a = 1$) and control ($a = 0$) groups
- X_Ω, X_t^a: covariate sets of the whole subjects (Ω) and treated/controlled subjects at t
- $\hat{y}_\Omega^a, \hat{y}_t^a$: regressors trained on oracle (Ω), and on collected data set at t
- Goal: Estimate $CATE(x) = E[Y^1 - Y^0 | X = x]$ with an estimator $\widehat{CATE}_t = \hat{y}_t^1 - \hat{y}_t^0$
- Original expected precision in estimation of heterogeneous effect (PEHE) includes the population $CATE(x)$, which makes analysis tricky. Define $\widehat{CATE}_\Omega = \hat{y}_\Omega^1 - \hat{y}_\Omega^0$.
- Suggest Bayesian PEHE:

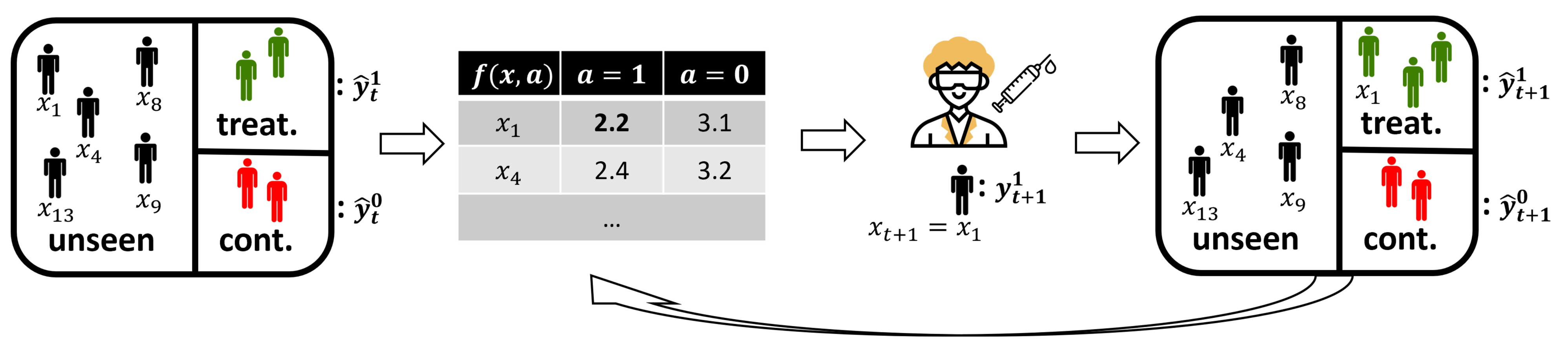
$$\epsilon_{PEHE}^{\Omega}\left(\widehat{CATE}_t\right) = \int_X \left(\widehat{CATE}_t(x) - \widehat{CATE}_\Omega(x)\right)^2 dP(x)$$

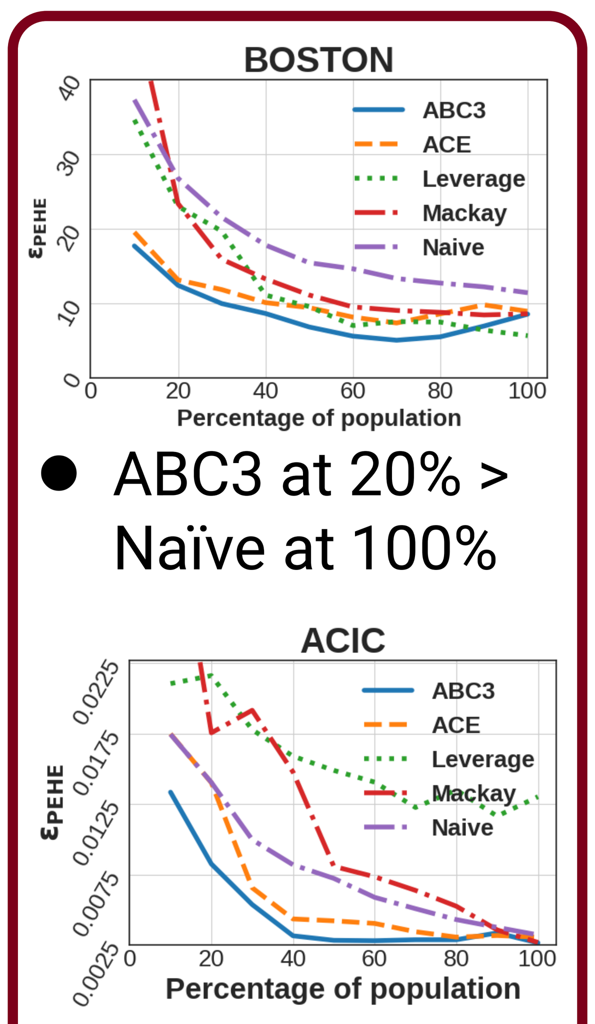
Algorithm: ABC3

- Goal: Find $x_{t+1} \in X_\Omega \setminus (X_t^1 \cup X_t^0), a_{t+1} \in \{0,1\}$, s.t. $argmin_{x_{t+1},a_{t+1}} E_{t+1}[\epsilon_{PEHE}^{\Omega}(\widehat{CATE}_t)]$
- **(Theorem)** Assume $Y^a \sim GP(0, k(x,x'))$, $\hat{y}_t^a(x) = E_t[Y^a(x)]$. Then under mild assumptions,

$$argmin_{x_{t+1},a_{t+1}} E_{t+1}[\epsilon_{PEHE}^{\Omega}(\widehat{CATE}_t)] = argmin_{x_{t+1},a_{t+1}} \int_X V_{t+1}[Y^1(x)] + V_{t+1}[Y^0(x)] dP(x)$$

  which is similar to Cohn criteria
- Thanks to GP, $V_{t+1}[Y^a(x)]$ does not depend on future outcome y_{t+1} (computable in prior)
- We also propose an efficient way to compute the target quantity (Proposition 4.2)



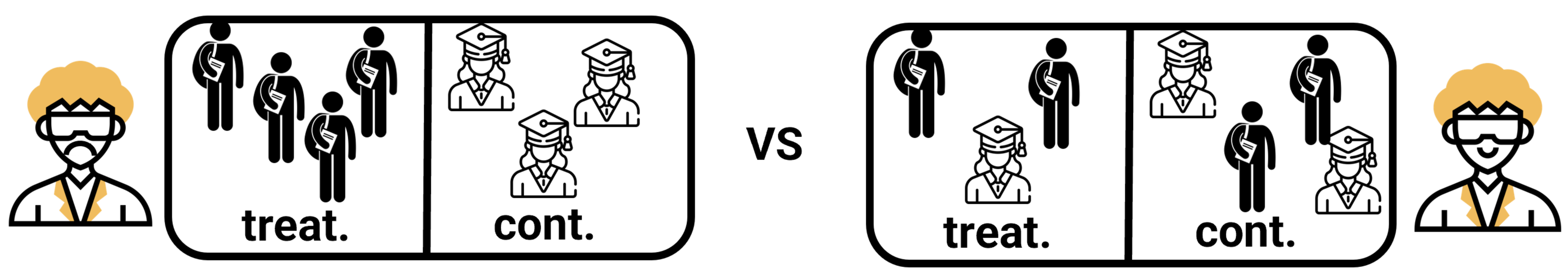


- ABC3 at 20% > Naïve at 100%
- ABC3 at 40% > Naïve at 100%

Theoretical Property

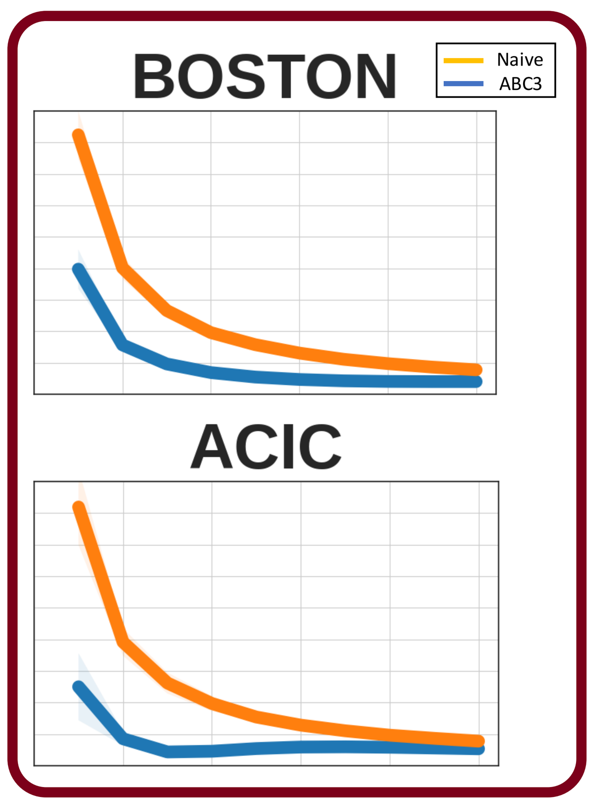
Balancing

- Balance between the treatment/control groups is crucial



- Maximum Mean Discrepancy(P,Q): difference of mean embeddings of P and Q in RKHS
- **(Theorem)** MMD(Treatment, Control) $\leq 4\left(\frac{\lambda^*}{|X_t^1|} + \frac{\lambda^*}{|X_t^0|}\right)$: minimized as time proceeds

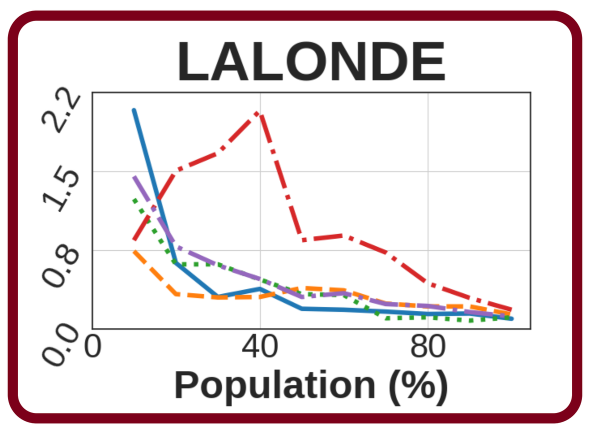
  $+2\int_X V_{t+1}[Y^1(x)] + V_{t+1}[Y^0(x)]dP(x)$: our optimization target



Type 1 Error

- Type 1 Error rate: $P_t[Type\ 1\ Error(x)] = P_t[|Y^1(x) - Y^0(x)| > \alpha]$, α: decision threshold
- **(Theorem)** Under Fisher's Sharp Null (i.e. $CATE(x) = 0$), ABC3 minimizes the upper bound of

$$\int_X P_{t+1}[Type\ 1\ Error(x)]\, dP(x)$$



Conclusion

- We introduce ABC3, an active learning algorithm for causal inference from Bayesian perspective
- ABC3 outperforms other algorithms by balancing treatment/control groups and minimizes type 1 error rate

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We have our oral presentation at March 2, 11:15am – 12:30pm, Reasoning Under Uncertainty session.

Code Personal